Kansei Design of Children's Products Integrating FKM and BPNN - A Case Study of Children's Microscope

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Abstract. Yiwu is a world-class market for small commodity production and sales, and its children's microscopes are cheap and fine. However, its product design is basically an imitation of popular market styles, and there is a problem of poor adaptability to the Kansei demands of children users. Based on the Kansei Engineering (KE) product styling design process, the exploratory method improvement was carried out, and a KE-FKM-BPNN children's product Kansei design system was constructed in this paper. Firstly, the styling elements of children's microscope were split by morphological analysis, and each component was digitally coded; Secondly, the numerical coding was used as the input layer of the Back Propagation Neural Network (BPNN). Thirdly, the fuzzy Kano model (FKM) was applied for quantitative analysis of the fuzzy Kansei images of children users, and the priority of children's Kansei demands was calculated. Finally, the nonlinear relationship model between microscope styling elements and child users' Kansei images was established based on the BPNN of Matlab. The experimental results show that this method can effectively obtain the priority of children's fuzzy Kansei images and predict the best combination of product styling design elements with the highest Kansei evaluation value. The reliability of the KE-FKM-BPNN children's microscope styling design system was verified by the experimental results. This method provides a favorable support for the styling design and modeling of children's microscope, improves the design efficiency, and solves the problem that designers cannot accurately design products based on the Kansei demands of children users.

Keywords: children's microscope, Kansei design, fuzzy Kano model, Kansei Engineering
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1 INTRODUCTION

Children's microscope plays a crucial role in basic science education, and it is an essential tool for children to explore biological science. The emotional design of children's microscope can help improve children's interest in scientific exploration. As a global center for small commodity production and manufacturing, Yiwu of China has become a world-renowned production and sales market for children’s microscopes due to its low price and reliable performance. Through the survey and interview in Yiwu International Trade City, it was found that there is a homogenization problem in the children’s microscope market. The styling design is mostly a imitation of popular market styles, and the product lacks innovative design. Gestalt psychology advocates describing consciousness and behavior with holistic image perception [1]. This theory can explain the intuitive cognitive mechanism of users for product styling, namely, the preference impression formed by sensory perception on product form factors, such as the points, lines, surfaces, blocks, materials, etc. of the styling. Therefore, designers need to characterize the specific style of a product with its specific styling features. In addition, the styling design of children’s microscope should depend on children’s cognitive characteristics, since children’s perception and aesthetics of products are different from those of adults. Facing the current situation of homogenization of children’s microscope styling, if children’s microscopes are designed from the perspective of children’s understanding of microscope styling, it can attract children’s attention, improve the satisfaction of children users, and increase their interest in scientific exploration.

The research on emotional design of product styling has gradually attracted the attention of the academic circle. Emotional design can improve the competitiveness of products, and accurate understanding of users’ emotional needs for products is particularly important [2]. In this paper, designers need to study children’s emotional preferences for the appearance of microscopes in order to design microscopes that meet the preferences of children consumers. Some scholars have proposed the theory of emotional design of product styling, including “emotional engineering”, “Kansei engineering”(KE), “affective design”, “affective ergonomics”, etc. [3] In the research of “Kansei Engineering” (KE), some words are usually used to express the emotional associations or psychological reactions brought by product styling to users, such as modern sense, fashion sense, cute sense, sense of technology, sense of stability, exquisite sense. To quantify the psychological feelings of users, questionnaires and scales are important methods and means to quantify users’ psychological feelings about product styling in the emotional measurement methods commonly used by Kansei engineering (KE). For example, American psychologist C·E·Osgood [4] proposed the SD method (Semantic Differential, SD) and Huang et al. [5] proposed the Semantic Differential Scale. This method does not require special instruments to perform experiments and obtain data, and the data is generally easier to process. Professor Noriaki KANO from Tokyo Polytechnic University proposed the KANO model [6], and believed that there is a non-linear relationship between the performance or service provided by a product and user satisfaction. The KANO model provides a new method for the research of user needs, through which quality classification and priority ordering of user needs can be performed. However, the psychological response brought by product styling to users often contains fuzzy elements. For example, some users are not sure how they feel about a certain product sample. They may have a certain degree of modern sense, but they may also have other feelings. Therefore, how to accurately obtain user’s priority needs is a vital task in the product development process. In addition, how to study the ambiguous psychological characteristics of users is also a key direction of this paper, especially for children users.

In recent years, the rapid development of artificial intelligence technology has brought new technical tools for the research of Kansei engineering. Firstly, based on the framework of Kansei engineering and combined with Artificial Neural Network (ANN) [7], the mapping relationship model between product design elements and Kansei information was established in this paper to realize the optimal design of microscope styling. Secondly, in order to study the ambiguity of children’s emotional preferences for product styling, the Fuzzy Kano model (FKM) was used to accurately identify and classify children’s emotional needs in this paper. To improve the product design process of ANN model, dimensionality reduction of evaluation items was realized by capturing the key Kansei demands of children users, thereby reducing the amount of information of ANN model algorithm training. Finally, by taking the styling design of children’s microscope as a study case, the proposed method also has certain universality for the styling design research of other children’s products, and can assist product designers in the styling design of children’s products.

2 LITERATURE REVIEW

2.1 Product Design Based on Kansei Engineering

There are many methods in the field of emotional research on product styling, among which Kansei engineering [3] is relatively mature in commercial application. Kansei Engineering (KE) originates from the "Emotion Technology" proposed by Japanese scholar Nagamachi, which mainly studies which product design features can induce specific emotions. The world's first Kansei engineering discipline was established at Shinshu University in Japan. "Kansei" is defined by the University of Tsukuba as "impression", which includes people's sense, feeling, psychological reactions and other factors [8]. Kenichi Yamamoto, Former Chairman of Mazda Motor Corporation, proposed the concept of KE in his speech titled "Car Culture Theory", and mapped users' emotional preferences for cars into the styling characteristics of cars by applying the mathematical statistics method and technique. In 1990, Ford Motor Company of the United States introduced KE into the process of automobile development [9]. In Asia, countries such as South Korea and Singapore have also applied KE to product design in recent years. The method of KE is generally divided into three steps: Firstly, the Kansei words of users are collected, and then the most relevant words are selected to construct the Kansei image space of users; Secondly, the relationship between Kansei words and product modeling elements is quantified by questionnaires; Finally, a prediction system is constructed using the Quantification Theory I（QTT-I）[10]. Regarding the application of KE in product design, Kittidecha [11] optimized the parameters of white wine glass modeling design to obtain user satisfaction. With the development of machine learning technology, the intelligent emotional design based on algorithm has gradually become a trend. For example, Yeh [12] established an association model between product color scheme and user emotion through ANN and Genetic Algorithm (GA).

2.2 Product Design Based on ANN

QTT-I [10] is a technique adopted by KE, which can explain the relationship between independent and dependent variables. If the relationship between independent and dependent variables is predicted to be non-linear, the accuracy of QTT-I will decrease [13]. In order to solve the limitations of QTT-I prediction technique in product Kansei design, some scholars establish a mapping model between product attributes and styles by combining KE with artificial neural network. Artificial Neural Network (ANN) is a computing system that attempts to imitate the neural connection in our nervous system. It was first proposed by Gallant, who also built the connectionist expert system [12]. Although simulating the human brain through ANN is still relatively rough, it is still visible that it has many similar characteristics to the human brain. Back Propagation Neural Network (BPNN) model is one of the commonly used ANN models. Each neural network (NN) consists of a group of interconnected artificial neurons, and is generally connected by three layers of input layer, output layer and hidden layer [14]. During the iteration process, the output result is compared with the desired value, and the resulting error signal is propagated back to gradually adjust the weights of each network connection until the specified error criteria are met. BPNN provides an effective means to check the complex relationship between input and output variables [15]. When the model training is completed, the root mean square error is used to analyze the prediction accuracy of the model. When the error is small, the output data becomes the predicted value. In recent years, the application of ANN has achieved excellent results. In the field of industrial product styling design, ANN can be used to simulate consumers' emotional reactions to products. Compared with the traditional multiple regression model technology of KE, ANN is a non-linear fitting method. Some industrial product design scholars obtain users' Kansei knowledge of product samples using NN, which provides a way to solve the "bottleneck" problem of knowledge acquisition in traditional KE. For example, Hsiao and Huang [16] proposed a product design method based on NN, and constructed the predictive relationship between product shape parameters and user emotion with BPNN. Lai and Lin [17] used the NN to construct a Kansei design system that includes the optimal combination of mobile phone shapes. Yeh C. H. et al. [18] proposed the application of ANN to provide designers with the optimal combination of shape element parameters of office chair that can map user's emotional images. Fu Guo et al. [19] built a quantitative relationship model between web interface design factors and user Kansei based on an ANN model. Literature review shows that ANN has good performance in Kansei evaluation, and the combination of ANN and KE is suitable for product styling design [20]. In this study, the NN model was used to investigate how to optimize the combination of microscope styling parameters to satisfy children's Kansei preferences.

2.3 Research on User Satisfaction Based on Kano Model

To improve user satisfaction with product or service needs, Noriaki KANO proposed a two-dimensional quality model based on Herzberg's motivation-hygiene theory, emphasizing to interpret the correlation between product quality and user satisfaction from a non-linear point of view. In the Kano model, the relationship between product quality and user satisfaction can be clearly understood by classifying product quality into Attractive Quality, One-dimensional Quality, Must-be Quality. As shown in Figure 1, the Kano's quality classification chart is described below. The horizontal axis represents the degree of quality sufficiency or insufficiency; The vertical axis represents satisfaction or dissatisfaction. In case of quality sufficiency, user satisfaction will significantly increase; While in case of insufficiency, users will not feel dissatisfied, and it is a potential demand of users [21].

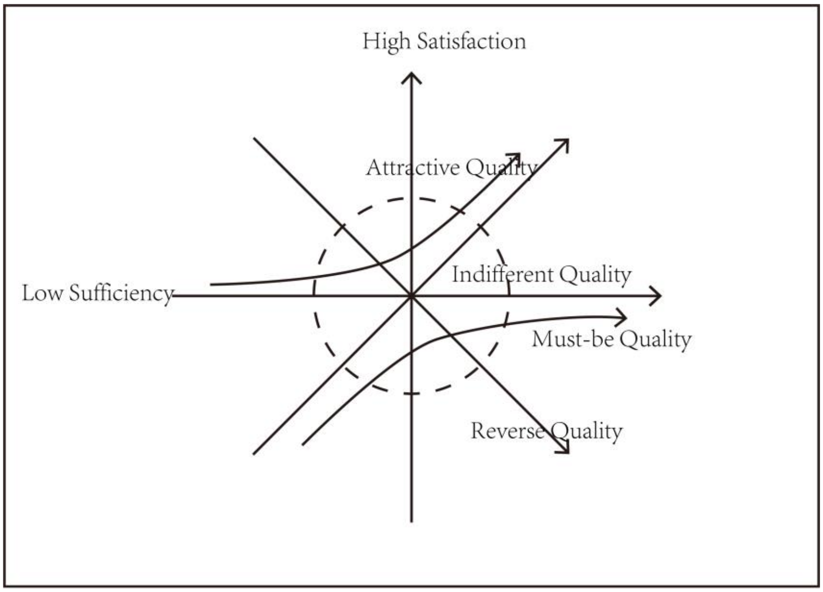


Figure 1: Kano model.

(1) Attractive Quality: In case of quality sufficiency, user satisfaction will significantly increase; While in case of insufficiency, users will not feel dissatisfied.

(2) One-dimensional Quality: The performance of this attribute has a linear relationship with user satisfaction. User satisfaction increases with sufficiency, while insufficiency will make users feel dissatisfied.

(3) Must-be Quality: Users consider this attribute to be a basic requirement. Satisfaction will not increase with quality sufficiency, but insufficiency will make users feel dissatisfied.

(4) Indifferent Quality: The sufficiency of this attribute has no impact on satisfaction.

(5) Reverse Quality: When this attribute is sufficient, the user will feel dissatisfied, and on the contrary, it will make the user satisfied.

(6) Questionable Quality: This result indicates that there are errors in the questionnaire or illogical evaluation values are given.

The relationship between product quality attributes and user satisfaction can be clearly understood through the above classification of product quality. For example, Ishardita Pambudi Tama et al. [22] analyzed the Kansei words that affect consumer satisfaction based on the Kano model, to improve the design of ceramic souvenirs. Tainyi (Ted) Luo et al. [23] explored the attractiveness of smart home products based on the Kano model. Wang Tianxiong et al. [24] studied the morphology of air purifiers using the fuzzy Kano. However, traditional Kano surveys cannot show the fuzzy spatial features of user thinking in detail, which may lead to incorrect classification results. Therefore, Lee et al. [25] applied the fuzzy theory to modify the traditional Kano questionnaire and proposed the FKM. The FKM has been applied to the field of product design by some scholars. For example, Yadav et al. [26] applied FKM to evaluate the aesthetic quality of vehicle appearance design, and proved that FKM can accurately classify consumers' emotional needs for automobile styling. Kang et al. [27] using the FKM to determine attractive attributes that have a remarkable influence on customer satisfaction and analyze customers' true needs therefrom.

3 THE PROPOSED RESEARCH FRAMEWORK

By taking children's microscope styling design as an example, the experience was divided into three phases, which are stated as follows: 1) the morphological analysis method [28] was applied for form deconstruction and coding of children's microscope; 2) The FKM was used to obtain the priority of Kansei words, and the SD was applied to evaluate the product samples by subjects under Kansei words; 3) The mapping relationship between Kansei words and product styling parameters was established using BPNN, and finally designers were guided for 3D modeling to complete verification.

3.1 Kansei Evaluation of Children's Emotional Needs

In order to analyze the emotional needs of children users for microscope styling design, the emotional needs of children users were classified through the FKM, and the emotional needs images were divided into corresponding quality attributes based on the results in this study. On this basis, the Attractive Quality was screened to achieve the purpose of clarifying the key needs of children users. The evaluation process of the FKM is shown below:

Step 1. The FKM questionnaire can have multiple choices, as shown in Table 1. According to the fuzzy feelings of respondents, the membership degree of the questions was assigned by percentage.

Certain Product Function	Like	Merited	Indifferent	Tolerable	Dislike
Realizable	0.7	0.3	0.1		
Unrealizable		0.1	0.3	0.6	

Table 1: Fuzzy Kano Questionnaire.

For example, the answer to the quality sufficiency and insufficiency of an emotional factor of the product can be described as: *Suf*=(0.7,0.3,0,0,0) and *ins*=(0,0,0.1,0.3,0.6).

Step 2. A 5 x 5 matrix can be obtained by matrix multiplication:

$$s=\begin{pmatrix} 0 & 0 & 0.07 & 0.21 & 0.42 \\ 0 & 0 & 0.03 & 0.09 & 0.18 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Step 3. After obtaining the matrix, the values of the matrix were matched against the attributes in the requirement attribute classification table (Table 2) proposed by Matzler and Hinterhuber. The two-dimensional quality classification in the matrix can be identified according to Table 2.

Criteria/Attributes		Insufficiency				
		Satisfied	Merited	Indifferent	Tolerable	Dissatisfied
Sufficiency	Satisfied	Q	A	A	A	O
	Merited	R	I	I	I	M
	Indifferent	R	I	I	I	M
	Tolerable	R	I	I	I	M
	Dissatisfied	R	R	R	R	Q

Table 2: Quality classification: A-Attractive, M-Must-be, I-Indifferent, R-Reverse, Q-Questionable.

Step 4. For the membership vector T of a category, the Kano quality attribute determination method for a certain question item is described below:

$$T=\{\frac{0.28}{A},\frac{0.18}{M},\frac{0.42}{O},\frac{0.12}{I},\frac{0}{R}\}$$

The value of confidence level a was introduced for further screening. If an element in the membership vector is greater than or equal to a, its corresponding demand is expressed by 1, otherwise it is expressed by 0. To ensure the condition and premise of less information crossing, the value was set as a=0.4. Therefore, the customer demand attribute vector was effectively screened by the value of a and converted to T=[0,0,0,1,0,0], indicating that the quality attribute represents an Indifferent Quality.

Step 5. Repeat the above steps for all survey users, and calculate the preference of each customer for the demand. The category with the highest frequency of demand preference is the corresponding demand item category of the quality attribute. When the final frequency is the same but cannot be distinguished, the priority ranking of demand categories follows the order of M>O>A>I [29].

3.2 BPNN Algorithm

The BPNN algorithm adopts a three-layer (input layer, hidden layer and output layer) network structure. The main characteristics of this network are signal forward feedback and error back propagation. In forward transmission, input signals are processed layer by layer from the input layer through the hidden layer to the output layer. The neuron state of each layer only affects the neuron state of the next layer. If the output layer does not get the desired output, it will shift to back propagation and adjust the network weight and threshold based on the prediction error, thereby making the predicted output of the BPNN close to the desired output. The topological structure of BPNN is shown in Figure 2.

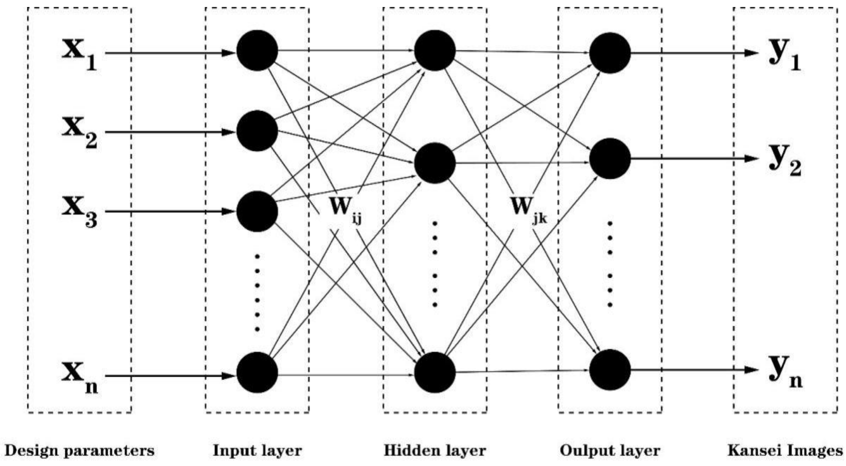


Figure 2: BPNN structure diagram.

Where, design elements X_1, X_2,..., Xn are the input values of the NN, Kansei Images Y_1, Y_2,..., Y_n are the predicted values of the NN, W_{ij} and W_{jk} are the weights of neurons from the input layer to the hidden layer, and from the hidden layer to the output layer, respectively.

Step 1. Determine the maturity of the network and the number of neurons in each layer: It is assumed that the network is a three-layer network architecture, and that the number of neurons in the input layer is N_{inp}, the number of neurons in the hidden layer is N_{hid}, and the number of neurons in the output layer is N_{out}.

Step 2. Initial weighted value and initial bias weight of the network: It is assumed that W_xh[i][h] is the weighted value between the i-th neuron in the input layer and the h-th neuron in the hidden layer, and W_hy [h] [j] is the weighted value between the h-th neuron in the hidden layer and the j-th neuron in the output layer. θ_h [h] is the bias weight of the h-th neuron in the hidden layer, and θ_y[j] is the bias weight of the j-th neuron in the output layer.

Step 3. Take the design elements of the microscope as the input value of the NN, and the consumer's Kansei images of the product as the prediction value of the NN. In the implementation process of NN, the input and output data should be normalized in order to solve the problem of inconsistent data scale. Since the output parameters of the training function need to be within the interval [0,1], and the user's Kansei evaluation results are not completely within this interval, Equation (1) was adopted to normalize the data and keep the experimental results within the appropriate interval.

$$X_k = (X_k - X_{\min}) / (X_{\max} - X_{\min}) \tag{1}$$

Where, X_{min} and X_{max} are the minimum and maximum values in the vector, respectively. Then input the normalized data into the hidden layer for calculation. Input training samples X [1], X [2], ..., X [N_{inp}] and target output values [T1] [T2], ..., T [N_{out}].

This study intends to use the Log-sigmoid function, as shown in Equation (2), to map the output value range between (0-1), where e is a fixed constant term.

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Step 4. Calculate the network output values Y[1], Y[2],..., Y[Nout]. The network output value of the hidden layer should be first calculated:

$$\mathrm{net}_{h[h]} = \sum_{i=1}^{N_{inp}} W_{xh[i][h]} \cdot x[i] - \theta\_h[h] \tag{3}$$

$$H[h] = \frac{1}{1+e^{-net\_h[h]}} \tag{4}$$

Where, net_h[h] is the weighted product sum of the h-th neuron of the hidden layer, and H[h] is the output value of the h-th neuron of the hidden layer. A nonlinear transformation was performed again for the collected weighted product sum net_h[h].

$$net\_y[j] = \sum_{h=1}^{N_{hid}} W_{hy[h][j]} \cdot H[h] - \theta\_y[j] \tag{5}$$

$$Y[j] = \frac{1}{1+e^{-net\_y[j]}} \tag{6}$$

Where, net_y[j] and Y[j] are the sum of the weighted products of the j-th neuron in the output layer and the output value, respectively.

Step 5. Calculate the difference between the output layer and the hidden layer.

$$\delta\_y[j] = Y[j] \cdot (1 - Y[j]) \cdot (T[j] - Y[j]) \tag{7}$$

Where, δ_y[j] is the error distance of the j-th neuron in the output layer.

Step 6. Update the weight and bias weight between layers.

Step 7. Repeat steps 3 through 6 until the network converges.

To verify the performance of the NN model, the mean square error analysis function MSE was used for performance test, and the expression is shown below:

$$MSE = \sqrt{\sum_j (T[j] - Y[j])^2 \Big/ N_{out}} \tag{8}$$

Where, *T* [*j*] is the target evaluation value, namely the value of Kansei words obtained through statistics after the participants fill in the questionnaire, Y[*j*] is the network output value, namely the value of Kansei words output by the NN, and Nout represents the number of neurons in the output layer. The MSE value of each Kansei word was calculated and tested by the function to verify the effectiveness of the network training model, so as to provide a reference for whether the product meets the Kansei demands of users.

4 CASE STUDY: CONSTRUCTION OF A STYLING DESIGN SYSTEM FOR CHILDREN'S MICROSCOPE

4.1 Data Preprocessing

Children's microscope was selected as a study case. Various styles of children's microscopes were collected and organized by the author through websites, e-magazines and retail stores. After removing poorly identified images, a total of 30 clearly visible children's microscope samples were retained. Next, the Adobe Photoshop software was used to process the images and remove the product color. According to the structure of product samples, 10 designers with more than 3 years of experience made a comparison, and 15 test samples with significant differences were obtained by eliminating those with high similarity.

Figure 3: 15 Samples of children's microscope.

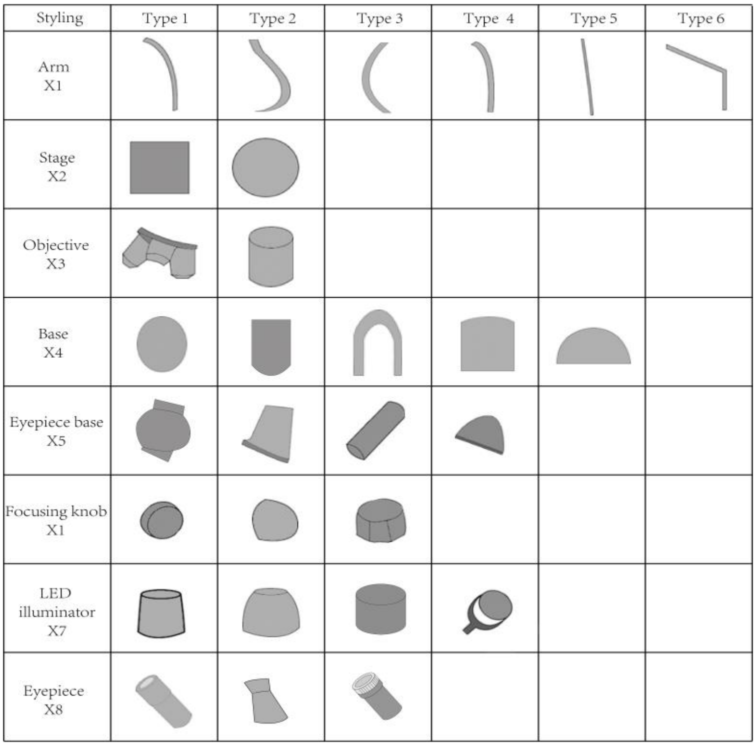


Figure 4: Morphological analysis of children's microscope.

4.2 Determination of Input Layer Indicators

In this study, the morphological analysis method [28] commonly used in Kansei Engineering was used to classify the morphological characteristics of products. The morphological analysis method was initiated by Swiss astronomer Fritz Zwicky [28], also known as the "morphological matrix method" or "checkerboard method". In this paper, the morphological characteristics of children's microscope were first broken down into several major components (items), and then each possible attribute (category) of each component was examined. As shown in Figure 4, the microscope was broken down into 8 items (arm, stage, objective lens, base, eyepiece base, focusing knob, illuminator and eyepiece). There were 6, 2, 2, 5, 6, 3, 4 and 3 design element types under the classification of the 8 items of the microscope, with 31 design elements in total.

Since the design elements cannot be directly used as input parameters of BPNN algorithm, the design elements of the microscope need to be encoded. The number of digits coded for each sample is the same as the total number of design elements, which is 31. In the code of each design element of the experimental sample, only one digit is 1, and the rest are 0. For example, if the design element types of sample 1 under 8 items are 1 (100000), 1 (10), 1 (10), 5 (00001), 4 (000100), 3 (001), 2 (0100) and 3 (001), respectively, the code of sample 1 is 10000010100000100010000101000010. Other samples are coded in the same way, and then used as input layer parameters of the BPNN, as shown in Table 3.

Sample No.	Arm	Stage	Lens	Base	Eyepiece Base	Focusing Knob	Illuminator	Eyepiece
Sample 1	000100	01	01	10000	001000	100	0100	100
Sample 2	000001	10	10	00001	000010	001	1000	100
Sample 3	001000	10	10	00001	000100	001	0010	001
Sample 4	010000	10	10	00100	010000	100	0100	001
Sample 5	001000	10	01	00001	001000	100	0001	100
Sample 6	000001	10	10	00001	001000	010	1000	100
Sample 7	000100	01	01	10000	000100	100	0010	010
Sample 8	001000	01	10	00010	000100	001	0010	001
Sample 9	000100	10	10	01000	000001	001	0100	100
Sample 10	001000	01	01	10000	000001	001	0100	100
Sample 11	001000	01	10	00100	100000	100	0010	100
Sample 12	000100	01	10	10000	000100	010	1000	100
Sample 13	001000	10	10	00100	001000	100	0001	100
Sample 14	001000	01	10	00010	000100	001	0010	100
Sample 15	100000	01	10	01000	000100	100	1000	100

Table 3: Coding of 15 training samples.

4.3 Determination of the Mean Value of Kansei Evaluation in Output Layer

Firstly, the Kansei words describing children's microscopes were summarized through user interviews, literature review and other methods, and then similar words were combined to obtain 12 representative Kansei words of children's microscope. Then, the KANO model analysis was performed according to the steps in Section 3.1 of this paper, and 100 questionnaires were prepared. Based on the collected data and the calculation method of the FKM, the final classification results shown in Table 4 were obtained. According to the results, "sleek and streamlined, simple and understandable, suitable and practical, curious and mysterious, amiable and cute, playful" are Attractive Quality and One-dimensional Quality that attract children users. This quality attribute can quickly improve user satisfaction.

Kansei Words	M	O	I	A	R	Q	Quality Attributes
1. Simple and understandable	18	39	14	4	1	0	O
2. Individualized	5	16	43	26	7	3	I
3. Smooth and superior	3	5	40	18	5	1	I
4. Suitable and practical	12	20	10	8	1	0	O
5. Steady	40	51	56	1	1	1	I
6. Cool	3	4	32	23	18	4	I
7. Sleek and streamlined	4	8	21	40	1	0	A
8. Playful	2	14	11	46	1	0	A
9. Labor-saving	0	4	30	15	2	0	I
10. Curious and mysterious	7	40	10	11	3	1	O
11. Amiable and cute	19	39	5	12	2	0	O
12. Vintage and retro	20	12	30	11	2	1	I

Table 4: Quality classification results of Kansei words based on FKM.

After determining 6 Kansei words, the Kansei evaluation values of 15 product samples were investigated by setting a questionnaire. In this paper, a 5-point SD method was used for questionnaire survey. The Kansei words of "sleek and streamlined, simple and understandable, suitable and practical, curious and mysterious, amiable and cute, playful" were used as the evaluation scale. The interval value of the scale was 1 to 5. Each subject scored 15 samples. Taking "simple and understandable" as an example, selecting 5 indicates a preference for "simple and understandable", selecting 3 indicates a neutral attitude towards the evaluation of the sample, and selecting 1 shows no preference for "simple and understandable". A total of 100 questionnaires were distributed and 90 valid questionnaires were collected. The data of 90 questionnaires were input into Excel for preliminary analysis, and the mean value of Kansei evaluation of 15 samples on "simple and understandable" was obtained. According to this method, the mean values of 6 Kansei evaluations of 15 samples were finally obtained, as shown in Table 5.

Sample No.	Arm	Stage	Lens	Base	Eyepiece Base	Focusing Knob	Illuminator	Eyepiece
Sample 1	000100	01	01	10000	001000	100	0100	100
Sample 2	000001	10	10	00001	000010	001	1000	100
Sample 3	001000	10	10	00001	000100	001	0010	001
Sample 4	010000	10	10	00100	010000	100	0100	001

Sample 5	001000	10	01	00001	001000	100	0001	100
Sample 6	000001	10	10	00001	001000	010	1000	100
Sample 7	000100	01	01	10000	000100	100	0010	010
Sample 8	001000	01	10	00010	000100	001	0010	001
Sample 9	000100	10	10	01000	000001	001	0100	100
Sample 10	001000	01	01	10000	000001	001	0100	100
Sample 11	001000	01	10	00100	100000	100	0010	100
Sample 12	000100	01	10	10000	000100	010	1000	100
Sample 13	001000	10	10	00100	001000	100	0001	100
Sample 14	001000	01	10	00010	000100	001	0010	100
Sample 15	100000	01	10	01000	000100	100	1000	100

Table 5: Mean values of Kansei evaluation of 15 training samples for children's microscope.

4.4 Model Initialization

The MATLAB was used to write BP network model program, the BP network model was trained and tested by inputting sample data, and the product styling design was predicted. The construction of BP network model was used to establish the relationship between Kansei images and styling design elements. The design elements of children's microscope were mainly classified by the morphological analysis method. The code of 31 morphological characteristic elements of children's microscope was taken as an input layer, that is, the input layer has 12 learning samples, each of which is composed of 31 neurons. By collecting and screening Kansei words, the 6 words of "sleek and streamlined, simple and understandable, suitable and practical, curious and mysterious, amiable and cute, playful" in the styling design of children's microscope were determined as the output targets of the NN. The evaluation values of 6 Kansei words of the first 12 samples in Table 5 were taken as the target output values, and there were 6 neurons in the output layer. In this paper, the number of nodes in the input layer is the type of 31 morphological design elements of children's microscope, and the number of nodes in the output layer is the number of Kansei words 6. Lin et al. [30] believed through research that when the number of neurons in the hidden layer is half of the sum of the number of neurons in the input layer and the output layer, the root mean square error value is small, according to which the number of neurons in the hidden layer was set as 19, so the initial structure of the model was 31-19-6.

4.5 BPNN Model Building and Testing

The number of training steps of BPNN model was set as 500, and the target error was 0.001. The neuron activation function is the Log-sigmoid function. The transfer function of the node is the Purelin function. The code data of the first 12 sample components and the evaluation values of Kansei words were taken as the training data set to train the product. The BPNN model was trained based on MATLAB software. The model converged at the 365th step of training to achieve the target error, as shown in Figure 5. The fitting effect of the training data is shown in Figure 6. It can be seen that 99% of the data are on the fitting regression line, and the model training effect is good.

4.6 Model Accuracy Test

Children's microscopes of samples 13, 14 and 15 in Table 5 were selected as test samples, which were input into the BPNN model to obtain the score of each Kansei word, and the error comparison was made with the score of artificial Kansei evaluation. See Table 6.

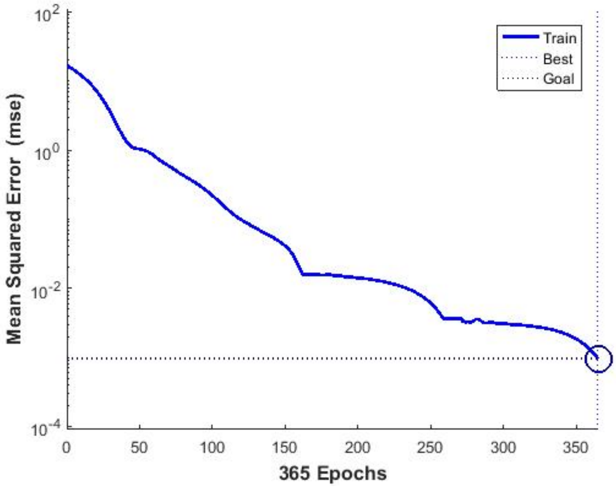


Figure 5: BPNN model training process.

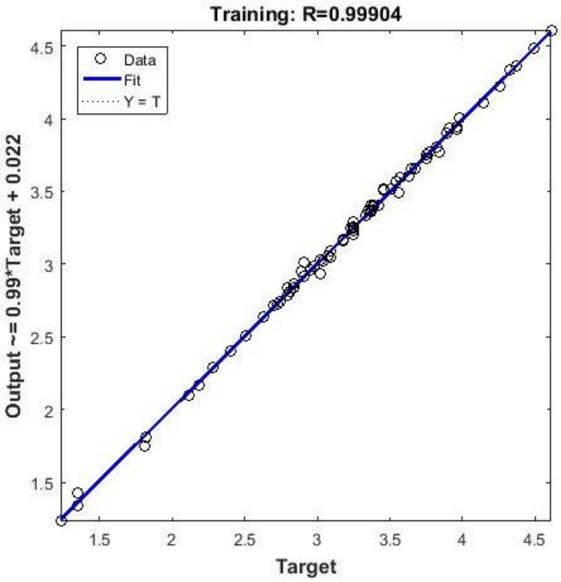


Figure 6: Fitting effect of training data.

Kansei Words Evaluation		Test Sample No.			MSE
		Sample 13	Sample 14	Sample 15	
Sleek and streamlined	Score of the subject	2.86	4.16	4.44	0.0096
	NN model score	2.74	4.25	4.36	
	Error absolute value	0.12	0.09	0.08	

Simple and understandable	Score of the subject	3.09	3.39	3.77	
	NN model score	3.12	3.51	3.74	0.0054
	Error absolute value	0.03	0.12	0.03	
Suitable and practical	Score of the subject	3.68	3.18	3.54	
	NN model score	3.64	3.28	3.42	0.0087
	Error absolute value	0.04	0.10	0.12	
Curious and mysterious	Score of the subject	2.65	3.33	2.72	
	NN model score	2.67	3.22	2.85	0.0098
	Error absolute value	0.02	0.11	0.13	
Amiable and cute	Score of the subject	2.09	3.47	3.96	
	NN model score	2.11	3.60	3.92	0.0063
	Error absolute value	0.02	0.13	0.04	
Playful	Score of the subject	1.68	3.63	3.70	
	NN model score	1.72	3.49	3.80	0.010
	Error absolute value	0.04	0.14	0.10	

Table 6: Predictive comparison results.

5 DISCUSSION

Through the styling design of the microscope, children are guided to observe the composition of objects they are familiar with using the microscope. The styling of a children's microscope can be divided into 8 parts, each of which has 6, 2, 2, 5, 6, 3, 4 and 2 types, which shows that there are $6\times2\times2\times5\times6\times3\times4\times2=17280$ kinds of basic morphological combinations for microscope styling. All the combinations were coded by computer and imported into the BPNN model as input layer parameters, and then the BPNN training set was used to fit the results, to calculate the corresponding Kansei evaluation value of each combination. After calculation, 6 groups of corresponding styling element combinations of "sleek and streamlined, simple and understandable, suitable and practical, curious and mysterious, amiable and cute, playful" were 32241233, 12221243, 61213322, 22215232, 22242111 and 22242141, respectively. From this, the optimal styling design solution under each Kansei word target can be judged. The optimal styling design results of 6 Kansei words can be predicted based on the KE-FKM-BPNN styling design system, which can be used as a guide for the styling design of children's microscope. Next, one of them was chosen to guide designers for 3D modeling, as shown in Figure 7, and the "simple and understandable" was taken as the styling design case. The simple style of the microscope makes it easy for children to understand how the product is used, and children can complete a series of operating tasks through only a few simple knobs. For example, the focusing knob (X6) adopts an egg-shaped design, which is suitable for children’s palm size and easy to grasp, and there are lines on the knob to indicate that it is a rotary knob. Ceramic materials have high temperature stability, corrosion resistance, high hardness and other characteristics, so they have been widely used in many fields. Quzhou white porcelain firing technique is the intangible cultural heritage of Zhejiang Province. Quzhou white porcelain is pure white and delicate, and the glaze color presents the texture of ivory white. In order to further enhance the material affinity of the product, Quzhou white porcelain firing technique is incorporated into our Kansei design scheme. The design scheme of children's microscope adopts the material of white porcelain texture, and various components of the product are connected together by black plastic connectors. The glaze color of white porcelain is pure and white, which helps children to focus on the operation without visual interference during the operation. The design of single eyepiece and simple objective reflects the function of the microscope simply and clearly. The very intuitive design makes it easier for children to use. The mirror is designed to look like a magnifying glass, so that children can understand how to operate easily. The integrated design of the product styling improves the integrity of the microscope, and children will not be distracted by trivial parts. The shape of the base resembles a cartoon character’s shoe, increasing the stability and interest. In the 3D model, the styling features were appropriately adjusted in the software Rhinoceros. In addition, by considering factors such as materials, the details were designed, and the model was imported into Keyshot for rendering. The effect is shown in the figure below. The products that meet the Kansei demands of children users were obtained through the KE-FKM-BPNN styling design system.

The way of questionnaire survey was adopted to verify the reliability of the KE-FKM-BPNN styling design system established in this paper. 30 child consumers were invited for questionnaire test. For the samples, Kansei measurement evaluation was conducted based on the Kansei word “simple and understandable”. The 5-point Likert scale was employed, and the mean value of questionnaire data was processed. The experimental data results show that the correlation coefficients of the ratio between the questionnaire result data and the BPNN output layer values were 0.9 ~ 1.0, indicating that the designed product can meet the individual Kansei demands of children users.

Previous product styling design based on KE generally transforms customers’ Kansei knowledge of product styling into product design elements. Existing literatures indicate that KE is suitable for product development, such as literatures [3, 8-11]. However, the architecture of traditional KE method still has some drawbacks and limitations. The traditional KE method cannot continuously quantify the relationship between Kansei information of product styling and design elements. For example, Wang [31] proposed a marine culture based creative product design based on KE. The architecture of KE is a linear regression model, which can hardly reflect the nonlinear relationship between customer subjective preferences and product styling design elements.

Relying on the basic architecture of traditional KE, the BP is applied for design research on product styling, to continuously quantify the nonlinear relationship between Kansei information and product styling design elements, so as to obtain the design prototype of children’s microscope that meets consumers’ expectations. Furthermore, a few scholars in existing researches have combined BP with the research framework of KE method for product Kansei design, such as literature [17]. KE-BP combines customer emotions with product design elements. Although these studies can quantitatively describe the predictive relationship between product styling Kansei image and design elements, which Kansei preferences of consumers will affect their purchasing decisions? How to analyze the Kansei preferences most influential for consumer satisfaction and then develop them into a key point of design? Therefore, in this paper, children’s microscope was taken as an example, to embed the FKM into KE, and build a product styling design system based on KE-FKM-BPNN, which can analyze the influence of consumers' Kansei preferences on product styling preferences. This is very important for customer-oriented product styling design.

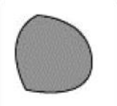
Sample No	Arm X1	Stage X2	Objective lens X3	Base X4	Eyepiece base X5	Focusing knob X6	Illuminator X7	Eyepiece X8
Simple and understandable	100000	01	01	01000	100000	010	0001	001
Styling features								

Figure 7: Styling design and modeling of "simple and understandable" children's microscope.

6 CONCLUSIONS

A KE-FKM-BPNN styling design system was built in this paper to assist in the styling design of children's microscope. Firstly, the Kansei demands information of children users was obtained based on KE, and the Kansei words were collected and screened to determine the Kansei words that have the greatest impact on children's microscopes, so that the microscope styling can be designed based on children's Kansei demands. Secondly, according to the Kano model theory, the demand attributes of users can be divided into Attractive Quality, One-dimensional Quality, Must-be Quality, Indifferent Quality, etc. Therefore, the children's Kansei demands information was set as evaluation items, and the quality attributes of these evaluation items were classified based on FKM model. By selecting 100 children for positive and negative questionnaire survey, the priority of children user needs was discussed. Thirdly, based on the strong self-learning and adaptive capabilities of BPNN, a microscope styling design based on the needs of children users was completed. First of all, the styling elements of children's microscope were split through morphological analysis, and each component was numerically coded; Then, the numerical coding was used as the input layer of the product BPNN, and the Kansei evaluation values of children's microscope were taken as output layer indicators to train the NN and verify the reliability of the model. Finally, through the precise predictability of the BPNN model, a styling design that meets the Kansei demands of children was completed. Compared to previous studies, the following four contributions are mainly made in this paper:

1. The KE and BPNN were combined to construct a styling design method for children's products, which solves the problem that designers cannot accurately complete product design according to user needs. The research method can help deeply understand the modeling style of children's microscope products, so as to reduce the children's product designers' trouble of lack of creative inspiration.

2. A method for screening evaluation items (Kansei words) based on FKM was proposed. This method further improves the product styling design process based on the KE-BPNN model, since in the KE phase, the greater the number of evaluation items, the greater the range of possible solutions in the BPNN algorithm, which greatly increases the speed of the algorithm. In order to solve this problem, the priority of users' Kansei demands was obtained by the FKM to further reduce the unimportant items, thus reducing the search range of BPNN algorithm, and improving the efficiency of product styling design.

3. Regarding the characteristics of fuzziness, complexity and uncertainty presented by Kansei demands of children users, the FKM was applied to realize accurate quantitative analysis of children's perceptual information as for how to accurately grasp the true emotional demands of children users. It should be noted that compared to adult users, there is a fuzzy space for children's perception of product form, or children may be fuzzy in language expression in the investigation of children's psychological feelings about product styling. Therefore, in view of the perceptual characteristics and expression limitations of children users, the FKM introduced in this paper effectively solves the deficiency of accuracy of Kansei information acquisition of KE for child users, which is a further expansion of the original research framework of Kansei engineering.

4. Taking children's microscope as a study case, the Kansei information of children users was converted into product styling features by the BPNN model to build the mapping relationship model between product design elements and Kansei information. The optimal design of adaptive combination of microscope styling was realized, and its effectiveness was verified. This model has a certain universality for the intelligent design of children's products, and provides design guidance and development reference for the design and development of children related products. It is helpful to design products that meet the needs of children consumers, and effectively avoid the shortcoming that product designers rely on subjective experience and cannot accurately grasp the psychology of children.

Only design elements are explored in this study, and the design of human-computer interaction of children's microscope will be studied based on the psychology of product design in the future. In addition, due to the limitations of BPNN, other algorithms can be integrated for improvement in the future research which is also the next research direction.

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